Journal of Business Research xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Research

A meta-analysis of correlations between market share and other brand performance metrics in FMCG markets

Sang-Uk Jung [a,*], John Zhu [b], Thomas S. Gruca [c]

[a] 107, Imun-ro, Dongdaemun-gu, Business School, Hankuk University of Foreign Studies, Korea
[b] Buell Management Bldg, M331, 21000 West Ten Mile Road, College of Management, Lawrence Technological University, Southfield, MI 48075, United States
[c] S356 Pappajohn Business Bldg., University of Iowa, Iowa City, IA 52242-1994, United States

ARTICLE INFO

Article history:
Received 11 August 2014
Received in revised form 28 April 2016
Accepted 29 April 2016
Available online xxxx

Keywords:
Empirical generalization
Meta-analysis
Double jeopardy
Category characteristics
Brand performance metrics

ABSTRACT

The strong relationship between market share and other metrics (i.e., penetration rate, purchase frequency, share of requirements) is well-documented in the marketing literature. However, there is no systematic meta-analysis of this important empirical generalization. This study quantifies the category-level correlations between market share and the aforementioned brand metrics. The category-level effects of promotional intensity, existence of sub-segments, purchase volume variation, and competition from private label and niche brands on these correlations are tested using grocery data from more than 400 categories. These factors have a negative effect all in three observed correlations with one exception. Promotional activity increases the correlation between market share and share of requirements. These results further generalize our knowledge of "Double Jeopardy" in FMCG markets and support the advice to brand managers to concentrate on increasing penetration rather than purchase frequency or share of requirements.

1. Introduction

Marketing research has well documented observed patterns of relationships among key measures of brand performance (Ehrenberg, Uncles, and Goodhardt, 2004). In markets for fast moving consumer goods (FMCG), high market share brands have correspondingly higher levels of penetration (more customers) than brands with low market shares. Furthermore, brands with lower market shares are purchased less frequently and their buyers are correspondingly less loyal (Fader and Schmittlein, 1993). Thus, the small share brand has multiple shortcomings due to its size (McPhee, 1963). This phenomena, often identified as Double Jeopardy (DJ), has been reported in more than 50 published studies (see Ehrenberg et al., 2004; Jung, Gruca, and Rego, 2010 for a listing).

Despite its long history, there remains a question about whether the observed relationships among brand performance measures meet the requirements of a "good" empirical generalization (Bass and Wind, 1995; Barwise, 1995). The most obvious shortcoming is in the formal measurement of the relationships between market share and other key brand performance metrics (e.g., penetration, purchase frequency, and share of requirements[1]). The existing literature documenting these relationships relies on researcher-identified patterns in the data. It does not utilize more formal and comprehensive meta-analytic methods typically used to generate empirical generalizations in marketing.

To bring additional rigor to research in this area, we quantify the relationships between market share and three key performance metrics (penetration, purchase frequency, share of requirements) using the Pearson correlation coefficient. Second, inter-category differences in the strength of these relationships are modeled using a number of category characteristics that moderate the relationship between market share and other metrics. The setting for this study is the U.S. grocery channel. Our data includes more than 400 FMCG categories.

This paper aims to make four salient contributions. First, it answers the calls (e.g., Ehrenberg et al., 2004; Kearns, Millar, and Lewis, 2000; Scriven and Bound, 2004; Doyle, Filo, McDonald, and Funk, 2013) to generalize the findings regarding the positive correlations between market share and three key performance metrics. Second, it extends the existing marketing theory regarding DJ by assessing these correlations and identifying boundary conditions for the observed relationships. Third, this is the first use of meta-analysis, specifically meta-regression (Hunter and Schmidt, 2004) on correlation measures

* Corresponding author.
E-mail addresses: sangukjung@gmail.com (S.-U. Jung), Thomas-gruca@uiowa.edu (T.S. Gruca).

[1] Also known as share of wallet, share of requirements is calculated solely among buyers of a specific brand. It is a given brand's share of purchase among all purchases made within the category by customers who have already purchased that brand.

http://dx.doi.org/10.1016/j.jbusres.2016.04.106
0148-2963/© 2016 Published by Elsevier Inc.

associated with the DJ phenomenon. Finally, by using a comprehensive database of brand performance metrics across more than 400 different FMCG categories, the results are generalizable and expand our knowledge about the strength of the relationships among key measures of brand performance.

The next section includes a review of the existing literature on the relationships among brand performance measures and its limitations. The subsequent section examines category-level determinants of the expected pattern of correlations among various measures of brand performance. The following section contains details on the data sources, study variables and empirical model. The results are followed by a discussion of their implications for managers. The paper concludes with study limitations and directions for future research.

2. Literature

2.1. Relationships between brand market share and key performance measures

The strong relationship between market share and other metrics (e.g. penetration rate) was first identified by McPhee (1963) for forms of entertainment (e.g. radio shows and movie stars). The same pattern was found in brand purchases over time by Goodhardt, Ehrenberg, and Chatfield (1984). He found that brands with smaller market shares had fewer and less loyal customers. Thus, a small share brand has multiple problems due to its size. While purchase frequency and purchase loyalty do vary somewhat with market share, these measures are more consistent across brands of varying market share than is the penetration rate (Ehrenberg et al., 2004; Sharp, 2010).

Despite the compelling evidence from various studies, the literature is still not conclusive with respect to the generalizability of the relationships among brand performance measures. A competing body of research has documented the existence of discrepancies (e.g., Bass and Wind, 1995; Kearns et al., 2000; Pare, Dawes, and Drisener, 2006) and called for a systematic examination on the deviations from the observed patterns (e.g., Ehrenberg et al., 2004; Kearns et al., 2000; Scriven and Bound, 2004; Doyle et al., 2013).

2.2. Limitations and proposed extension of current research

2.2.1. Metrics to quantify the strength of the relationships

The first and most obvious shortcoming in this stream of research is the lack of quantification of the relationships between market share and other key brand performance metrics (penetration, purchase frequency, share of requirements, etc.). For example, Uncles, Ehrenberg, and Hammond (1995) describe the following buying patterns in FMCG categories: “The market shares differ greatly.” “The brands also have very different numbers of buyers, in line with their market share.” “In contrast, the average purchase frequencies are much more similar.” “But, there is a small downward “Double Jeopardy” (DJ) trend with market share.”

In a discussion of developing empirical generalizations, Bass and Wind (1995) identify a hierarchy of approaches starting with informal “eye balling” of data to identify regular patterns and ending with formal meta-analysis of empirical results. The existing evidence documenting and discussing the presence of strong relationships among brand performance measures in FMCG markets is much closer to the informal “eye ball” approach than other methods used in generating empirical generalizations.

This limitation is problematic since research on confirmation bias suggests that, “People tend to seek information that they consider supportive of favored hypotheses or existing beliefs and to interpret information in ways that are partial to those hypotheses or beliefs” (Nickerson, 1998). Therefore, researchers interested in documenting these patterns are more likely to report on findings consistent with their favorable predisposition.

In this study, correlations between market share and three key brand performance metrics – penetration, purchase frequency and share of requirements – are computed and analyzed across categories. This allows statistical modeling of these relationships (central tendencies and variances). Using correlations provides objective measurement about whether or not a given pattern is actually present. Furthermore, meta-analysis can be used to test for regularities in the deviations from the observed relationships between market share and other performance metrics.

2.2.2. Boundary conditions for the observed pattern

A second limitation in research on relationships between market share and other brand performance measures is a lack of systematic studies to identify boundaries conditions for the observed patterns among market share and other brand measures. While scholars working in this related area suggest that deviations from the overall patterns are “rare” (Ehrenberg, Goodhardt, and Barwise, 1990), there are a number of studies documenting deviations (Fader and Schmittlein, 1993; Bhattacharya, 1997; Scriven and Bound, 2004; Pare et al., 2006; Pare and Dawes, 2007, 2008; Jung et al., 2010). A review of these studies and others (e.g., Kahn, Kalwani, and Morrison, 1988) suggests that number of brand offerings, performance of niche brand and private labels, promotional activities, variability of purchase volume, overall penetration, purchase frequency and product stockpilability within a category could affect the relationships between market share and other brand performance metrics. In this study, we assess whether these category factors affect the relationships between market share and other metrics that can be determined using meta-regression (Hunter and Schmidt, 2004).

3. Factors affecting the strength of the relationships between market share and other brand measures

Prior research has identified a number of factors that may reduce the strength of the relationship between market share and one of the key brand metrics (penetration, purchase frequency, and share of requirements). When market share or any of other three metrics changes disproportionately under the influences of these factors, the correlations across brands are changed, generally weakening the expected relationship. The effect of each factor is briefly discussed next.

3.1. Number of offerings

Within a category, multiple brands are offered to accommodate for customers' varying needs and budgets. The extant models used to study the DJ phenomenon assume that all brands in a category are competing with each other (e.g., Goodhardt, Ehrenberg, and Chatfield, 1984). However, more offerings in a category likely indicate highly diversified positions across competing brands. For instance, a “good, better, best” strategy involves offering a selection differentiated by price and quality (e.g., Banquet, Stouffer's, and Marie Callender's in the frozen foods category). Highly price segmented markets may also include brands positioned to appeal to the “super premium” buyer (e.g., Häagen-Dazs ice cream). If there are sub-markets within a category, some comparatively low share brands will have higher or lower than expected penetration. This would reduce the observed correlation between market share and the other metrics (penetration, purchase frequency and share of requirements).

3.2. Promotional activity

Promotional activity may distort the expected relationship between a brand's penetration rate and the level of repeat purchases (Bhattacharya, 1997; Danaher, Wilson, and Davis, 2003). If a brand offers deep discounts or is promoted through features or displays, these promotions may effectively change the purchase pattern of existing consumers. Intensive promotional activity may attract the marginal buyer who purchases the product only once. As such, these “one-off” purchases increase a brand's penetration rate while affecting its average purchase rate or share of requirements as well. Therefore, we expect to observe more deviations from the expected patterns of high correlations in those categories with high levels of promotional activity.

3.3. Niche brand share

A niche brand seeks to appeal to a narrow set of customers who become avid consumers of the off-beat product. This results in a low penetration but a high level of purchase frequency (Kahn et al., 1988). This violates the commonly observed pattern of a positive relationship between market share and penetration/frequency, which requires penetration/frequency moves on par with market share, neither too low nor too high. Within a category, if more sales are achieved by niche brands, a bigger share of the market sales will gravitate towards irregular low penetration with high purchase frequency. The expected relationships between market share and performance measures of penetration, frequency and loyalty across all brands are likely to be distorted and lead to deviations from the expected strong positive relationship. As such, the presence of these types of brands within a category may reduce the correlations between market share and other brand performance measures.

3.4. Variability in purchase volume

If there are wide variations in the volume per purchase occasion across brands in a category, brands with certain level of penetration/frequency are likely to have fairly different market shares, which weakens the relationship between market share and penetration/frequency.

Furthermore, previous research shows that given penetration and market share, deviations in share of requirements is related to brand-level differences in purchase volume (Bhattacharya, 1997; Jung et al., 2010). Thus, in categories with a wide range of purchase volumes across brands, the expected relationship between market share and share of requirements would be lessened.

3.5. Private label brand share

Unlike many manufacturer brands which are available across the country, the distribution of private label products are restricted to the store chain with which they are associated (Bound and Ehrenberg, 1997; Pare and Dawes, 2007). However, due to mass-market positioning and the retail support that each store chain offers to its own private label brands, the penetration and share of requirements for private labels are often higher than national brands within a given chain (Bound and Ehrenberg, 1997; Uncles and Ellis, 1989). At the chain level, national brands tend to have lower average market shares, penetration and share of requirements compared to the store chain's private label offering. The same pattern often holds when aggregated across store chains, which leads to disproportionate changes in market share and other performances for all brands including private labels across the entire grocery channel. Hence, the observed correlations are expected to be lower within categories with high levels of private label sales for the whole grocery channel.

3.6. Category penetration

Higher category penetration implies that brands in the category are in general successful in acquiring customers to buy the product, but it may also indicate that buyers tend to be less loyal to specific products (Narasimhan, Neslin, and Sen, 1996). That is, buyers are more likely to seek variety or respond more actively to promotional activities and switch to other brands. As such, in these categories, national brands tend to have difficulty in achieving high market share, which in turn changes (weakens) the relationship between market share and other market performance metrics. Therefore, more deviations from high correlations between market share and other performance metrics in categories with high category level penetration are expected.

3.7. Category purchase frequency

Buyers who purchase more often tend to have lower switching cost because they can switch back to their preferred products in a shorter time (Bawa and Shoemaker, 1987). It is relatively costless and of low risk to switch and try other brands, as one mistake in brand choice only ruins only one purchase out of many. Due to lower switching costs, buyers in a category with higher purchase frequency are more likely to react to promotional activities and have lower brand loyalty. This change of purchase pattern results in disproportionate changes in market share versus other performance metrics and reduces the correlations between market share and other brand performance measures.

3.8. Stockpilability

Buyers in categories that can be stockpiled readily are more likely to respond strongly to promotional activities because it is directly related to the mechanism of purchase acceleration (Litvack, Calantone, and Warshaw, 1985). Stockpilable products have a long shelf-life. Hence, consumers tend to take advantage of deals and purchase a large quantity during promotional periods. This buying acceleration can affect the key performance metrics among competing brands which have different promotional calendars. As such, the correlation between market share and other brand performance measures will be weaker in categories with higher stockpilability.

4. Data and measures

The data for this study comes from the IRI Consumer Insights Builder. This database combines store level scanning data with panel purchases from some 50,000 households in the United States. These data are for the grocery store channel. We have a cross-sectional sample of annual, national-level measures for all variables. The aggregation at brand level (instead of individual level) of the raw data is appropriate for our study, which requires input of complete and accurate brand level performance measures. Our data comes from the year 2000 and includes the universe of FMCG categories and brands in the grocery store channel at that time.

Using a comprehensive set of brands allows us to derive generalizable results. Typically, meta-analysis is performed on a collection of published and unpublished studies. Using a single data source ensures that all moderating variables are present for all observations. The usual drop off in sample size is avoided as is the problem of unreported results (i.e., the file drawer problem).

The data are organized hierarchically. At the highest level are eight store departments: bakery, dairy, deli, edible grocery, frozen foods, health and beauty, non-edible grocery, and general merchandise. Within each department, there are a large number of categories for example, coffee in the edible grocery category. However, within most categories, there is a further subdivision of brands into sub-categories. For example, in the coffee category, brands are further divided into ground coffee, ground decaffeinated, instant, instant decaffeinated, and whole coffee beans. For our study, the unit of analysis is at the subcategory level (hereafter we will refer to them as categories). At this finest level of distinction, we are more likely to have an unsegmented market, a key assumption underlying prior research (Goodhardt et al., 1984).

To validate our results, we used several screening criteria for our datasets following previous studies (Fader and Schmittlein, 1993; Bhattacharya, 1997; Jung et al., 2010; Kahn et al., 1988). We limited our analysis to those brands with a national market share larger than 1%. Private labels were treated as brands and included in the calculation for market share. We also limited our analysis to categories with more than three brands and those which are purchased at least three times a year. Finally, the set of brands in each category had to account for at least 80% of all purchase volume. These criteria narrowed the universe of FMCG brands and categories to 4573 brands in 427 categories. This set of brands accounts for 69% of all FMCG sales volume in $'s in 2000.

IRI data provides our key brand performance measures of penetration, purchase frequency, and share of requirements (SOR) which are defined as follows respectively:

$$\text{Penetration}_i = \frac{\text{Number of People who Buy a Brand } i}{\text{Market Population}} \tag{1}$$

$$\text{Purchase Frequency}_i = \frac{1}{\text{Average Purchase Cycle of Brand } i} \tag{2}$$

$$\text{Share of Requirements}_i = \frac{\text{Number of Purchase of Brand } i}{\text{Total Category Purchase by brand } i \text{ Buyers}}. \tag{3}$$

Number of offerings[2] is measured as the number of brands in the category. It is an indicator for potential presence of brand tiers or submarkets within the category when all brands try to differentiate from each other and satisfy different customer needs and budget requirements.

There are multiple measures of promotional activity available in the IRI data. For this study we used the *average price discount* in the category and *overall level of promotional activity*. The average price discount is the average percentage off the non-discounted price. The level of a promotional activity is indicated by the percent of volume purchased on any deal including price discounts, features, displays and coupons (and combinations thereof). [Results were similar using percentage of volume sold on feature, display or coupon. Details are available from the authors.]

A small firm or a small division of a large company takes the niching strategy for a brand to avoid head-to-head competition with the market leaders. A niche brand is positioned to serve a small number of loyal customers, and normally of low market share (Kahn et al., 1988). To identify niche brands, we rely on the following criteria proposed by and used by Bhattacharya (1997) and Danaher et al. (2003):

$$\text{Niche}_i = \frac{\text{w}_i(1-\text{b}_i)}{\sum_i \text{MS}_i \text{w}_i(1-\text{b}_i)} \tag{4}$$

where i refers to each brand in the category, w_i, b_i and MS_i are the purchase frequency, the penetration and market share of brand i respectively. Following extant literature (Bhattacharya, 1997; Kahn et al., 1988; Danaher et al., 2003), we define a niche brand as one whose ratio is greater than 1.1, which implies that it has a high purchase frequency relative to its penetration. On average, the niche brands account for 16% of all brands in each subcategory.

For the meta-analysis, we take the measure of *niche brand share* by summing up the market shares of all niche brands (in the unit of %, i.e. a 3% takes the value of 3). We first add 1 to calculated raw measure and then make the natural log-transformation to reduce the effects of outliers. The addition of 1 makes the log-transformed value to exist for those categories that did not contain any niche brands (i.e. 0% market share for niche brands).

To measure the *variability in purchase volume* across brands in a category, we computed the volume-weighted standard deviation of (average) purchases per year.

In the IRI data, the shares of all private label brands are reported as a single aggregate. Therefore, each private label is treated as one brand and included in the market share calculation for each category. To assess the influence of private label brands in the meta-regression, we measure *private brand share* as the (log-transformed) share of private label brands within a category.

Category penetration is the average share penetration (computed as the percentage of sample households who purchase the brand) for all brands within the category.

Category purchase frequency is computed as the inverse of the average purchase cycle (number of purchases) of the product per year.

Following prior studies, *stockpilability* is defined as the degree of easiness to stockpile (Litvack et al., 1985). Two professional coders were recruited to code the measure for each product category. It takes the value of −1, 0, and 1 to represent high, neutral, low of *stockpilability* respectively.

We also include *category share* to control for the total share of brands in a subcategory which have market share larger than 1% and included in the study.[3]

Tables 1 and 2 provide the summary descriptive statistics for our dataset.

5. Results and discussion

5.1. Pattern and variance of correlations

As Table 2 shows, there is significant and negative correlation between the three correlation measures ($\text{Correlation}_{(\text{market share-penetration})}$, $\text{Correlation}_{(\text{market share-purchase frequency})}$, $\text{Correlation}_{(\text{market share-share of requirements})}$) and most of the predictors (category characteristics). This provides a preliminary non-model support for hypothesized patterns.

To estimate the (population) correlation of market share with penetration, purchase frequency and share of requirements across FMCG categories, we used the Hunter-Schmidt estimate (Hunter and Schmidt, 2004).

The estimates of the population correlation and its variance are presented in Table 3 Details of the estimation procedure are included in the note of Table 3.

It is clear that market share and penetration are highly correlated, with a correlation of 0.941. The correlations of market share/purchase frequency (0.537) and market share/share of requirement (0.618) are both significantly positive. High market share brands have correspondingly high levels of penetration. The levels of market share and the other metrics (purchase frequency and share of requirements) are also positively related. Overall, these results from more than 400 FMCG categories provide strong evidence of a DJ pattern. Smaller brands have fewer customers, are purchased less frequently and have less loyal customers, as measured by share of requirements.

At the same time, the relationship between market share and the other metrics is less pronounced than with penetration. In other words, levels of purchase frequency and share of requirements are higher for higher share brands. But across all brands, the smaller

[2] There is a concern of partial circular relationship among the independent and dependent variables because covariates such as the number of brands and niche brand share measure is logically (and algebraically) related to one or more of performance measures. This concern is alleviated because our dependent measures are the correlations between market share and three other performance measures (penetration, purchase frequency, and share of requirements) instead of the raw measures directly. The statistics from the correlation matrix (Table 2) further alleviate this concern of confounding. Specifically, correlations between *number of offerings* with three dependent measures are between −0.35 and −0.29, and correlations between *niche brand share* with three dependent measures are between −0.25 and −0.10. All of them are within acceptable range. The issue of potential circularity is further address by the addition of the comprehensive category characteristics as controls in our model.

[3] By dropping small brands, we are effectively removing a number of observations (accounting for 31% of the brands) with effectively zero (or close to it) share. This may reduce the observed correlations because, for these brands, the measures of penetration, purchase frequency, and share of requirements tend to be at low levels. Including this control variable helps to correct for the potential bias.

Please cite this article as: Jung, S.-U., et al., A meta-analysis of correlations between market share and other brand performance metrics in FMCG markets, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.04.106

Table 1
Descriptive statistics (N = 427).

Variable	Mean	Standard deviation	Median
Correlation$_{\text{(market share-penetration)}}$	0.95	0.09	0.97
Correlation$_{\text{(market share-purchase frequency)}}$	0.57	0.30	0.62
Correlation$_{\text{(market share-share of requirements)}}$	0.66	0.26	0.71
Number of offerings	10.71	5.09	10.00
Promotion-price discount	24.84	4.99	24.62
Promotion-level of promotional activity	25.73	10.74	25.10
Niche brand share	2.72	1.28	3.00
Variability in purchase volume	0.54	0.61	0.34
Private label share	2.49	1.16	2.65
Category penetration	36.64	22.31	33.05
Category purchase frequency	3.21	2.02	2.70
Stockpilability	−0.12	0.71	0.00
Market share	8.35	11.13	3.82
Share of requirements	42.34	19.25	40.42
Category share	90.55	6.29	91.54

Table 3
Hunter Schmidt meta-analysis results.

Variable	Mean of $\bar{r}$	Var_{corr}	Var_{e}	Reliability (r)
Correlation$_{\text{(market share-penetration)}}$	0.941	0.007	0.001	0.197
Correlation$_{\text{(market share-purchase frequency)}}$	0.537	0.078	0.052	0.666
Correlation$_{\text{(market share-share of requirements)}}$	0.618	0.064	0.039	0.612

Note: Estimates of population correlation is given by: $\bar{r} = \frac{\sum_i N_i r_i}{\sum_i N_i}$, where r_i is the correlation in the ith category and N_i is the number of observations (brands) in the ith category. The variance of population correlations (Var_{corr}) is given by subtracting sampling error (Var_{e}) from the variance of sample correlations (Var_{r}): $\text{Var}_{\text{corr}} = \text{Var}_{\text{e}} - \text{Var}_{\text{e}} = \frac{\sum_i [N_i (r_i - \bar{r})^2]}{\sum N_i} - \frac{(1-\bar{r}^2)^2}{\bar{N}-1}$, where the estimate of the population correlation ($\bar{r}$) is given in Eq. (1), and $\bar{N}$ is the average number of observations across categories. In this case, the number of brands in a category is equal to the number of observations.
Some of the variance in the estimate of the population correlation is due to sampling error. Hunter and Schmidt (2004) provide an approach to assess how much of this variance is due to sampling error. The first step is to compute the sampling error variance (Var_{e}) which is given by the following formula: $\text{Var}_{\text{e}} = \frac{(1-\bar{r}^2)^2}{(\bar{N}-1)}$, where $\bar{r}$ is the estimate of the population correlation from Eq. (1) and $\bar{N}$ is the average number of observations across categories. These results are also presented in Table 3.
The ratio of the variance of the population correlation (Var_{r}) and the sampling error variance (Var_{e}) provides an estimate of the reliability of the correlations across studies (categories). In other words, this ratio shows what percentage of the variance in the estimate of the population correlation is due to sampling error (Hunter and Schmidt, 2004). If this ratio is greater than 75%, there are not likely to be significant moderating factors across the individual studied. This ratio is also provided in Table 3. We see that the ratio is lower than 75% for all of the correlations between market share and the other brand performance metrics. Thus, factors other than sampling error account for significant part of the variance in the estimate.

correlations show that differences in these metrics is less extreme than we observe when comparing penetration across brands with differing levels of market share.

These results should be of great interest to brand managers. These findings show that observed differences in market shares are more likely to be related to variations in penetration rather than be influenced by purchase frequency or share of requirements. This serves as an important empirical generalization because it provides a quantitative benchmark for managers to assess the likely impact of changes in various brand performance metrics on market shares at the retail level.

We next describe our meta-analysis to determine how the factors described above (e.g., presence of niche brands) affect the observed correlations.

5.2. Meta-analysis

To identify how category characteristics discussed above influence the correlations between market share and other brand performance metrics, we estimated random/mixed meta-regression across categories. Let c_i and t_i denote the estimated and true correlation coefficients in ith category respectively. Considering some errors in estimation, this relationship can be expressed as following:

$$c_i = t_i + \varepsilon_i \tag{5}$$

where $\varepsilon_i \sim N(0, \sigma_i^2)$.

We assume that the variation in t_i across categories follows the normal distribution around the linear predictor. That is, true correlation coefficients can be explained by some category specific characteristics:

$$t_i = \beta_i x_{i\kappa} - u_i \tag{6}$$

where $u_i \sim N(0, \tau^2)$.

Because this random/mixed meta-regression is a special case of GLS, so it can be fitted using a two-step approach of GLS (Raudenbush, 2009). First, we use the restricted maximum-likelihood estimator (REML) for the estimation of τ^2. For the estimation of β, we use the weighted least squares with weights equal to $w_i = \frac{1}{v_i + \tau^2}$, where v_i denotes the sampling variance and τ^2 denotes the estimate of τ^2.

Following Pigott (2012), the dependent variable for the model is that Fisher Z-transformation of the correlation coefficient for the ith

Table 2
Correlations.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Correlation$_{\text{(market share-penetration)}}$	1.00												
2. Correlation$_{\text{(market share-purchase frequency)}}$	.18‡	1.00											
3. Correlation$_{\text{(market share-share of requirements)}}$	.24‡	.44‡	1.00										
4. Number of offerings	−.31‡	−.29‡	−.35‡	1.00									
5. Promotion-price discount	−.02	−.06	−.00†	.09	1.00								
6. Promotion-level of promotional activity	−.16	−.07†	.02†	.02	−.28‡	1.00							
7. Niche brand share	−.10†	−.25‡	−.11†	−.04	−.02	−.15‡	1.00						
8. Variability in purchase volume	−.17‡	−.03	−.07	.04	−.02	.03	−.03	1.00					
9. Private label share	−.06†	−.18‡	.06	.05	.06	.09	−.13‡	.06	1.00				
10. Category penetration	.01	.17‡	.16‡	.39‡	.16‡	−.10†	−.21‡	.07	−.33‡	1.00			
11.Category-purchase frequency	−.15†	.17	.23‡	.30‡	−.02	.13†	.15†	.05	−.28‡	.33‡	1.00		
12. Stockpilability	.01	−.03	−.02	.08	.13†	.22‡	−.04	.20‡	.00	.01	−.10	1.00	
13. Subcategory share	.17‡	.24†	.27‡	−.36‡	.17‡	−.17‡	.12†	−.04	−.08	−.04	−.01	.06	1.00

‡ $p < 0.001$.
† $p < 0.05$.

Please cite this article as: Jung, S.-U., et al., A meta-analysis of correlations between market share and other brand performance metrics in FMCG markets, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.04.106

Table 4
Parameter estimates for the meta-regression.

Category factors	Dependent variables		
	Correlation (market share-penetration)	Correlation (market share-purchase frequency)	Correlation (market share-share of requirements)
Intercept	2.48***	0.89***	1.79***
Number of offerings	−0.05***	−0.05***	−0.07***
Promotion-price discount	−0.01	−0.02*	−0.01
Promotion-level of promotional activity	−0.05	−0.05*	0.06^
Niche brand share	−0.02^	−0.01***	−0.01
Variability in purchase volume	−0.02***	0.01	−0.01**
Share of private label share	−1.97*	−1.22***	−1.94***
Category penetration	−0.01**	−0.01***	−0.01^
Category purchase frequency	−0.05**	0.01	−0.05***
Stockpilability	0.06	0.01	−0.04^
Category share	0.04	0.06	0.03
Adj. R^2	0.48	0.71	0.74

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
^ $p < 0.1$.

category. Therefore, the original correlation measure with value between [−1, 1] is mapped in to a range of [−∞, ∞], which is appropriate for regression analysis.

The results are presented in Table 4. Overall, three correlations are affected similarly by the independent variables we examined.

For the correlation between market share and penetration, a large number of brand offerings in the category has a significant negative effect (−0.05, $p < 0.001$) as do variability in the purchase volumes across brands (−0.02, $p < 0.001$), the market shares of private label products (−1.97, $p < 0.05$), niche brands (−0.02, $p < 0.1$), category penetration (−0.01, $p < 0.01$) and category purchase frequency (−0.05, $p < 0.01$). These results are all in the expected direction. However, we fail to find significant negative effects of promotion-price discount, promotion-level of promotional activity and stockpilability on correlation between market share and penetration.

To better demonstrate the effects of contingencies (moderators) for the correlation, we computed the marginal effects of each contingency on the raw correlation coefficient. Specifically, we computed the marginal change of each contingency at the mean of each transformed correlation, and make backward conversion to get the marginal effects in the unit of raw coefficient. Table 5 summarizes the results. In that regard, the effects of contingencies are more interpretable and meaningful. For instance, holding all other independent variables constant, 1% increase of share of private label share is associated with a 0.96% decrease in the correlation between market share and penetration. The similar marginal effect computation is made for the other two correlations and reported in the same table.

For market share and purchase frequency, the higher the number of brand offerings (−0.05, $p < 0.001$), depth of price discounts (−0.02, $p < 0.05$), and level of promotional activity in the category (−0.05, $p < 0.05$), the lower the correlation between those two performance metrics. Also, the higher the market shares of private label products (−1.22, $p < 0.001$), niche brands (−0.01, $p < 0.001$) and category penetration (−0.01, $p < 0.001$), the lower the observed correlation. Moreover, there are no significant negative effects of variability in purchase volume, category purchase frequency, and stockpilability on this correlation.

Looking at the results for market share and share of requirements, we see that the number of brand offerings (−0.07, $p < 0.001$), variability in purchase volume (−0.01, $p < 0.01$), market shares of private label (−1.94, $p < 0.001$), category penetration (−0.01, $p < 0.1$), category purchase frequency (−0.05, $p < 0.001$), stockpilability (−0.04, $p < 0.1$) all have a significant negative effect on the observed correlation. We do not find significant negative effects of promotion-price discount or niche brand share. A surprising result is that in categories with a high level of promotional activity, the correlation between market share and share of requirements is significantly higher (0.06, $p < 0.1$). This is counter to the conventional belief that a high level of promotional activity within a category would erode a brand's loyalty and thereby reduce the observed share of requirements. However, the measure of promotional activity is volume weighted. This suggests that high share brands sell a high proportion of their volume on some sort of promotion (feature, display, etc.). We conjecture that the effect of promotional deals in FMCG categories is to raise the share of requirements (brand loyalty)

Table 5
Marginal effects of key variables.

Category factors	Dependent variables		
	Correlation (market share-penetration)	Correlation (market share-purchase frequency)	Correlation (market share-share of requirements)
Number of offerings	−0.05***	−0.05***	−0.07***
Promotion-price discount	−0.01	−0.02*	−0.01
Promotion-level of promotional activity	−0.05	−0.05*	0.06^
Niche brand share	−0.02^	−0.01***	−0.01
Variability in purchase volume	−0.02***	0.01	−0.01**
Share of private label share	−0.96*	−0.84***	−0.96***
Category penetration	−0.01**	−0.01***	−0.01^
Category purchase frequency	−0.05**	0.01	−0.05***
Stockpilability	0.06	0.01	−0.04^

* $p < 0.001$.
** $p < 0.01$.
*** $p < 0.05$.
^ $p < 0.1$.

Please cite this article as: Jung, S.-U., et al., A meta-analysis of correlations between market share and other brand performance metrics in FMCG markets, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.04.106

for market leading brands. This would be an interesting subject for future research.

6. Conclusions

Bass (1993) emphasized the importance of empirical generalization in marketing science by discovering "a pattern or regularity that repeats over many different circumstances." The pattern of high correlations between marketing share and other measures of brand performance identified in numerous isolated studies of FMCG markets generalizes to a very wide range of product categories in the U.S. grocery channel. Since our data spans more than 400 product categories, this study add significantly to our body of knowledge about this important phenomenon. Our results quantify the relationships between market share and three other key brand performance metrics via the Pearson correlation (computed across brands). We find that the relationship between market share and penetration is much stronger compared that of purchase frequency or share of requirements. At the same time, there are significant deviations in some product categories. The divergent opinions in prior literature about the generalizability of the DJ phenomena (e.g., Ehrenberg et al., 2004; Pare et al., 2006; Scriven and Bound, 2004; Doyle et al., 2013) are likely due to sample bias when individual categories (instead of the population of categories) were chosen for study.

Beyond a straightforward meta-analysis of these correlations, we also examined a comprehensive list of category factors (i.e. that number of brand offerings, performance of niche brand and private labels, promotional activities, variability of purchase volume, overall penetration, purchase frequency and product stockpilability) that influence the strength of the relationships between market share and the other brand performance metrics. Any set of existing findings arising from a small subset of categories or competitive conditions need to be validated to check its generalizability. A systematic replication on a larger scale is likely to detect any variation, bias or outliers in the expected pattern. Our study serves as both an indirect replication and extension of the prior research in related literature on double (DJ) jeopardy.

The boundary conditions identified in this study assist managers to fine-tune the judgment on the expected strength of relationship when the brand level information is incomplete for the category. When important decisions of brand strategy and optimized resource allocation are to be made jointly, our research will be an essential resource for identifying the effective tactics to achieve specific objective(s). For instance, when we set market share (or sales revenue) as the objective and the same magnitude of improvement can be achieved with investment in customer acquisition (change of penetration) and brand loyalty (change of share of requirement). Our results suggest that the firm might be better off spending money in acquiring new customers because of the relatively high correlation between market share and penetration rather than trying to boost loyalty.

Lastly, when firms make crucial decisions on brand portfolio management, such as launching a new brand, extending a brand or brand deletion, the category characteristics indicate to the firm the expected deviations from expected pattern. This information enables the decision makers to make "if… then…" predictions, and compare outcomes of all alternatives associated with brand management in different contexts. Hence, firms will be in a better position to leverage their capability and resource in order to optimize these portfolio decisions and achieve performance goals.

Like all empirical studies, this one has limitations that invite future research efforts. First of all, we based our study on only one year of data. Due to the evolving dynamics in the retail market place, there might be longitudinal deviations in the study effects, which cannot be addressed out using multiple years of data. Future research with more updated data of similar quality should serve as a replication of these findings and further investigate recent market dynamics. Second, the current study covers all information in the grocery channel. These findings likely hold rigorously for brands sold in grocery channel. However, the application of these results to other channels such as drugstores or mass merchandisers should be done with caution. Third, our data does not include important information that might affect the performance of brands at the national level such as geographic availability (%ACV distribution). Fourth, the findings do not necessarily hold for high-end consumer products or highly specialized products given our use of FMCG dataset. Future studies on products in relevant categories are warranted to provide generalized findings and theoretical extensions. Finally, these results are but a first step. Showing that market share is strongly correlated with penetration rate is one thing. Truly understanding how brand managers, retailers and customers all interact to influence that key metric is quite another.

Acknowledgement

This work was partially supported by Hankuk University of Foreign Studies Research Fund.

References

Barwise, P. (1995). Good empirical generalization. *Marketing Science*, *14*(3–2), G29–G35. http://dx.doi.org/10.1287/mksc.14.3.G29.

Bass, F. M. (1993). The future of research in marketing: Marketing science. *Journal of Marketing Research*, *30*(February), 1–6. http://dx.doi.org/10.2307/3172509.

Bass, F. M., & Wind, J. (1995). Introduction to the special issue: Empirical generalizations in marketing. *Marketing Science*, *14*(3–2), G1–G6. http://dx.doi.org/10.1287/mksc.14.3.G1.

Bawa, K., & Shoemaker, R. W. (1987). The effects of a direct mail coupon on brand choice behavior. *Journal of Marketing Research*, *24*(4), 370–376. http://dx.doi.org/10.2307/3151384.

Bhattacharya, C. B. (1997). Is your brand's loyalty too much, too little, or just right?: Explaining deviations in loyalty from the Dirichlet norm. *International Journal of Research in Marketing*, *14*(5), 421–435. http://dx.doi.org/10.1016/S0167-8116(97)00024-4.

Bound, J. A., & Ehrenberg, A. S. C. (1997). Private label purchasing. *Admap*, *375*, 17–19.

Danaher, P. J., Wilson, I. W., & Davis, R. A. (2003). A comparison of online and offline consumer brand loyalty. *Marketing Science*, *22*(4), 461–476. http://dx.doi.org/10.1287/mksc.22.4.461.24907.

Doyle, J. P., Filo, K., McDonald, H., & Funk, D. C. (2013). Exploring sport brand double jeopardy: The link between team market share and attitudinal loyalty. *Sport Management Review*, *16*, 285–297.

Ehrenberg, A. S. C., Goodhardt, G. J., & Barwise, T. P. (1990). Double jeopardy revisited. *Journal of Marketing*, *54*(July), 82–91. http://dx.doi.org/10.2307/1251818.

Ehrenberg, A. S. C., Uncles, M. D., & Goodhardt, G. J. (2004). Understanding brand performance measures: Using Dirichlet benchmarks. *Journal of Business Research*, *57*(12), 1307–1325. http://dx.doi.org/10.1016/j.jbusres.2002.11.001.

Fader, P. S., & Schmittlein, D. C. (1993). Excess behavioral loyalty for high-share brands: deviations from the Dirichlet model for repeat purchasing. *Journal of Marketing Research*, *30*(November), 478–493. http://dx.doi.org/10.2307/3172692.

Goodhardt, G. J., Ehrenberg, A. S. C., & Chatfield, C. (1984). The Dirichlet: A comprehensive model of buying behaviour. *Journal of the Royal Statistical Society, A*, *147*, 621–655. http://dx.doi.org/10.2307/2981696.

Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*. Thousand Oaks, CA: Sage.

Jung, S. U., Gruca, T., & Rego, L. (2010). Excess loyalty in CPG markets: A comprehensive examination. *Journal of Empirical Generalisations in Marketing Science*, *13*(1), 1–13.

Kahn, B., Kalwani, M., & Morrison, D. G. (1988). Niching versus change-of-pace brands: Using purchase frequencies and penetration rates to infer brand positioning. *Journal of Marketing Research*, *25*(November), 384–390. http://dx.doi.org/10.2307/3172949.

Kearns, Z., Millar, S., & Lewis, T. (2000). *Dirichlet deviations and brand growth*. Gold Coast: Proceedings of the Australian and New Zealand Marketing Academy Conference.

Litvack, D. S., Calantone, R. J., & Warshaw, P. R. (1985). An examination of short-term retail grocery prices effects. *Journal of Retailing*, *66*, 9–25.

McPhee, W. (1963). *Formal theories of mass behavior*. New York, NY: The Free Press of Glencoe.

Narasimhan, C., Neslin, S. A., & Sen, S. K. (1996). Promotional elasticities and category characteristics. *Journal of Marketing*, *60*(2), 17–30. http://dx.doi.org/10.2307/1251928.

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology*, *2*(2), 175–219. http://dx.doi.org/10.1037//1089-2680.2.2.175.

Pare, V., & Dawes, J. (2007). Deviations from double jeopardy: how many private label and high share brands exhibit excess loyalty? *Proceedings of the Australian and New Zealand Marketing Academy Conference*. New Zealand: Otago.

Pare, V., & Dawes, J. (2008). Do all private label brands exhibit excess loyalty? *Proceedings of the Australian and New Zealand Marketing Academy Conference*. Australia: Sydney.

Please cite this article as: Jung, S.-U., et al., A meta-analysis of correlations between market share and other brand performance metrics in FMCG markets, *Journal of Business Research* (2016), http://dx.doi.org/10.1016/j.jbusres.2016.04.106

Pare, V., Dawes, J., & Drisener, C. (2006). Double jeopardy deviations for small and medium share brands – how frequent and how persistent? *Proceedings of the Australian and New Zealand Marketing Academy Conference*. Australia: Brisbane.

Pigott, T. D. (2012). *Advances in meta-analysis.* New York, NY: Springer Verlag. http://dx.doi.org/10.1007/978-1-4614-2278-5.

Raudenbush, S. W. (2009). Adaptive centering with random effects: An alternative to the fixed effects model for studying time-varying treatments in school settings. *Journal of Education, Finance and Policy*, *4*(4), 468–491. http://dx.doi.org/10.1162/edfp.2009.4.4.468.

Scriven, J., & Bound, J. (2004). A discussion of Dirichlet deviations. *Proceedings of the Australian and New Zealand Marketing Academy Conference*. New Zealand: Wellington.

Sharp, B. (2010). *How brands grow: What marketers don't know.* South Melbourne: Oxford University Press.

Uncles, M. D., & Ellis, K. (1989). The buying of own labels. *European Journal of Marketing*, *23*(3), 57–70. http://dx.doi.org/10.1108/EUM0000000000561.

Uncles, M. D., Ehrenberg, A. S. C., & Hammond, K. (1995). Patterns of buyer behavior: Regularities, models and extensions. *Marketing Science*, *14*(3), 71–78. http://dx.doi.org/10.1287/mksc.14.3.G71.